Geol. Soc. Malaysia, Bulletin 36, December 1994; pp. 55-59

Improved characterisation of carbonate reservoirs using non-linear modelling

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Abstract: Physical properties of reservoir rocks such as type of lithofacies, porosity and permeability, are directly related to the recoverable volumes of hydrocarbons. Therefore it is important to determine these properties as accurately as possible. These properties however, can only be directly measured on cores of which, for economic reasons, only a limited numbers are available for a gas/oil field. Open hole logs on the other hand, are available in most wells and therefore it is common practice to derive the reservoir properties by calibrating the log responses to the core measured properties.

Common techniques such as multi-variate linear regression are not always successful for carbonate reservoirs due to diagenetic effects that can strongly affect the relationship between reservoir properties such as porosity and permeability.

To improve the determination of carbonate reservoir properties from logs, the use of non-linear modelling was investigated with commercially available PC based software. Use of this user-friendly technique has proved useful in the prediction of the type of lithofacies and reservoir permeability and results in a better estimate of reservoir properties.

INTRODUCTION

When calculating permeabilities from open hole log responses, often the following conventional technique is used: firstly, the porosity is calculated from one or several open hole log responses and subsequently, the porosity-permeability relationship as measured on cores is used to calculate the permeability.

Whereas this technique often works satisfactorily for clastic rocks, it is often hampered by lithofacies type dependency and diagenetic effects in carbonate rocks. Figure 1 shows the typical porosity-permeability data of a Miocene carbonate buildup. Clearly a single porosity-permeability relationship, whether linear or non-linear, does not sufficiently describe the core measured data. Each of the lithofacies types (illustrated by different colors) forms more or less a separate cluster, with some overlap between the clusters. Ideally, one would like to apply a separate relationship per lithofacies type. Studies have shown however, that conventional multi-variate linear regression techniques are not successful in distinguishing between the lithofacies based on open hole log responses.

For rock properties modelling such as permeability and lithofacies type, one would like to include all available input parameters that have a possible, but unknown effect on the properties to be modelled. Examples of input parameters are the open hole logs, reservoir fluid type, drilling mud type and geological zone coding. However, as seen in Figure 1, non-linear behaviour can not be excluded. For these reasons, a tool is needed to cater for such modelling where the number of input parameters is large, to discard a parameter if it has a non-significant impact, and to handle non-linear relationships.

A software package AIM (Abductive Induction Mechanism, see reference) is one of such tools that was used for this study. This PC based package offers a user-friendly way to derive non-linear models from a database of examples. Such a database can be core plug measured data with the corresponding log responses.

DATA PREPARATION AND NETWORK MODELLING

Like the majority of these studies, the preparation of the data is of prime importance. When the permeability is correlated to open hole log responses, it is important that the core plug measured permeability is right on depth with the open hole log responses. Also, the results will improve when outliers in the datasets are removed, like erratic log responses and non representative core measured data. The latter can be due to for example damaged plugs. Once the database is depth matched and the outliers removed, the database can be imported into the AIM modelling package.

Before synthesising a model, the available database is normally split into a training dataset (70% of the data) and an evaluation dataset (30% of

Presented at GSM Petroleum Geology Seminar '93

the data). The training dataset will be used to derive the model whereas the evaluation dataset can be used for later verification of the network performance.

The modelling process is userfriendly and fully automated. Statistically non-significant parameters are automatically discarded. The final network model, a sequence of linear and/or polynomial equations, is a balance between accuracy (describing the training data as accurate as possible) and robustness (satisfactory performance on yet unseen data like the evaluation dataset). In Figure 2, a schematic representation is included of a network. Once a network is obtained with a satisfactory prediction for the evaluation dataset, the set of equation can be output as an embeddable C code routine.

EXAMPLE

Several problems with characterisation of carbonate rocks were investigated, two of which are discussed here:

1. Modelling of permeability

Instead of deriving the permeability from a porosity-permeability relationship as shown in Figure 1, a network was synthesised to model the permeability from several open hole logs. Although the database included density, neutron, gamma-ray and resistivity log responses, log derived porosity (calculated from density and neutron log responses) and reservoir fluid content, the resulting network used the log derived porosity, gammaray and density logs only. The permeability as modelled by the network provides a better match with the core measured data, this is clearly observed in Figure 3. Investigations in other carbonate reservoirs also resulted in improvements over conventionally derived permeabilities.

2. Modelling of lithofacies type

Earlier attempts using linear statistical techniques to distinguish between lithofacies based on open log responses were unsuccessful. In a particular Miocene carbonate buildup, the reservoir was cored in two wells and the geological description of the cores resulted in six different types of lithofacies: tight lithofacies, mouldic limestone, chalky mouldic limestone, chalky limestone, mouldic dolomite and mouldic dolomitic limestone. Available open hole logs that could be included in the evaluation were the density, neutron, sonic and resistivity logs, separation between the density and

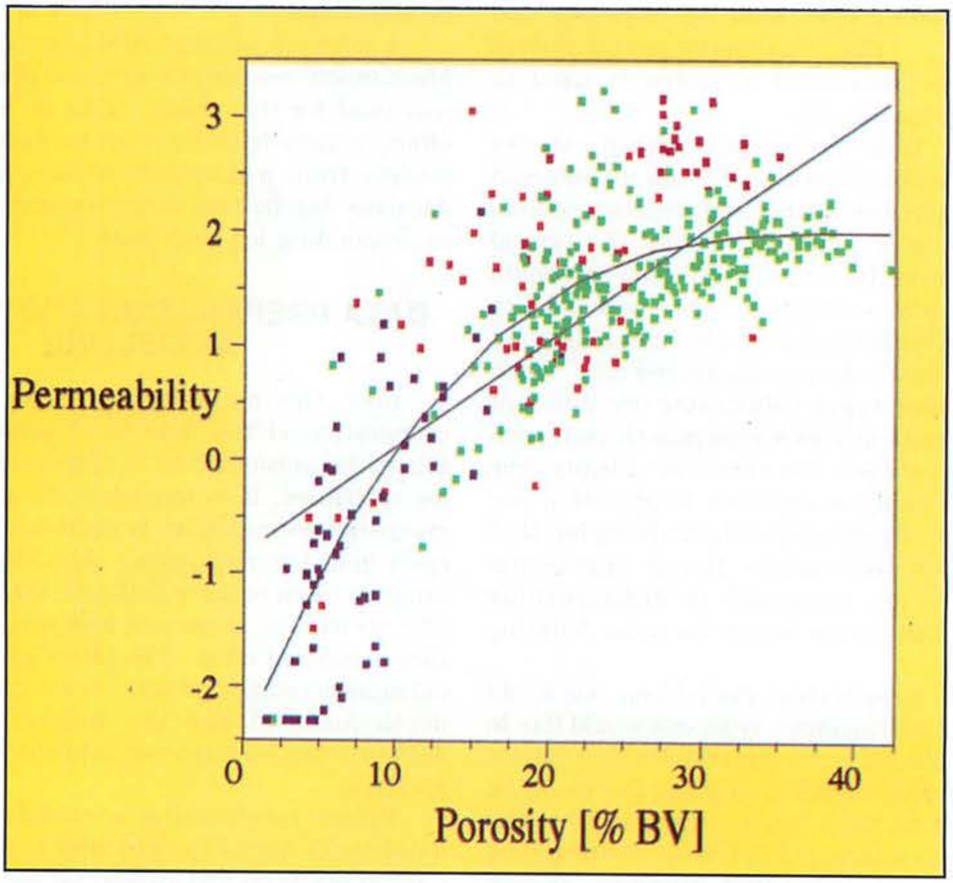

Figure 1. Core measured porosity and permeability data from a Carbonate buildup.

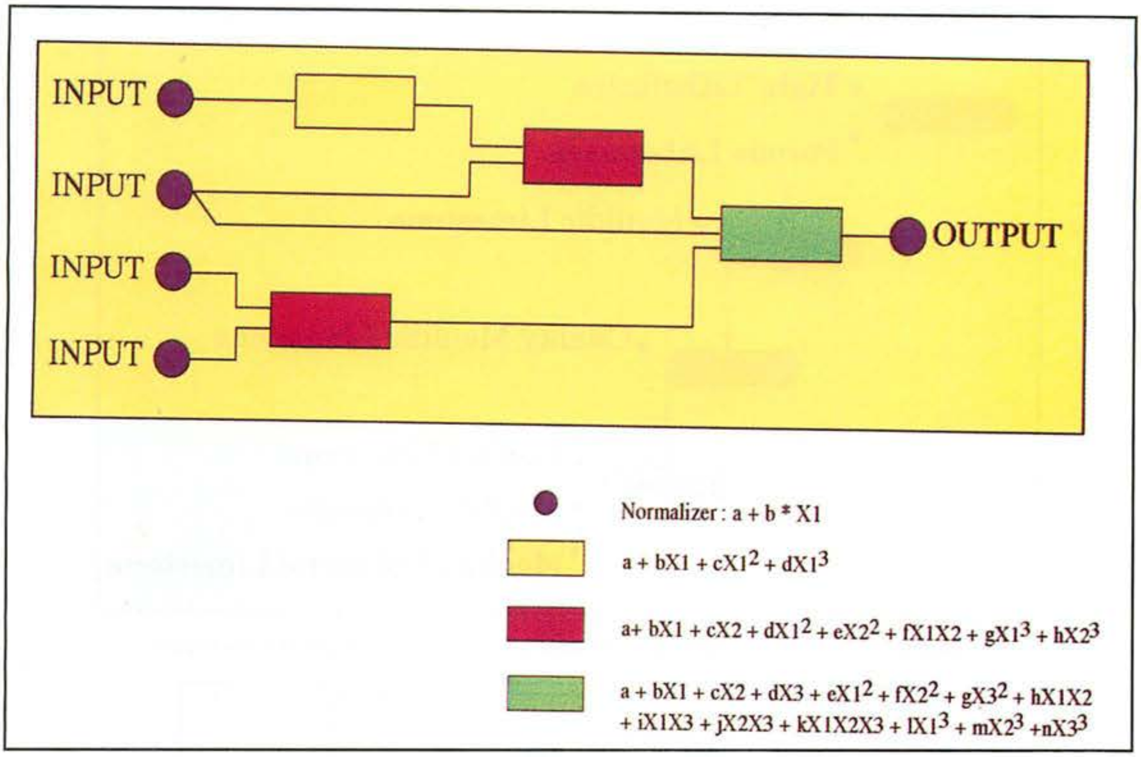

Figure 2. Schematic representation of a non-linear network.

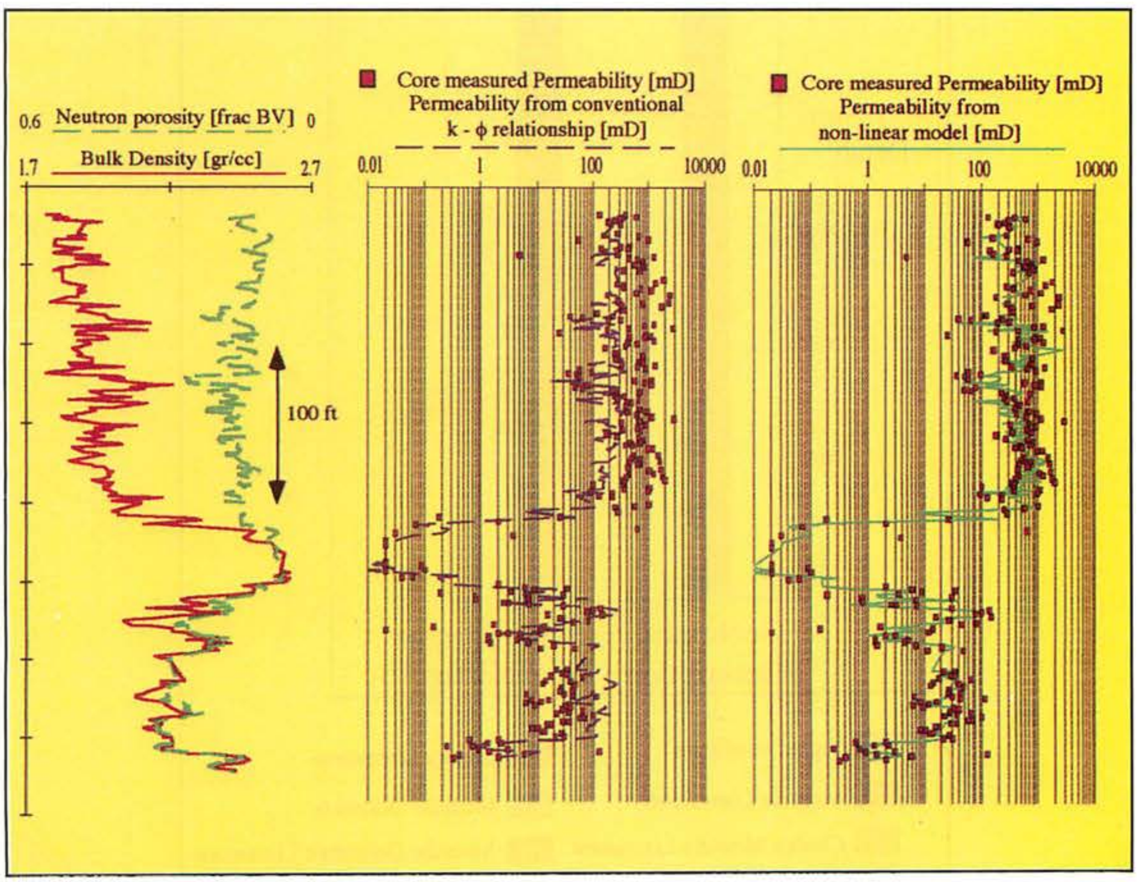

Figure 3. Comparison between conventional and non-linear modeled permeability.

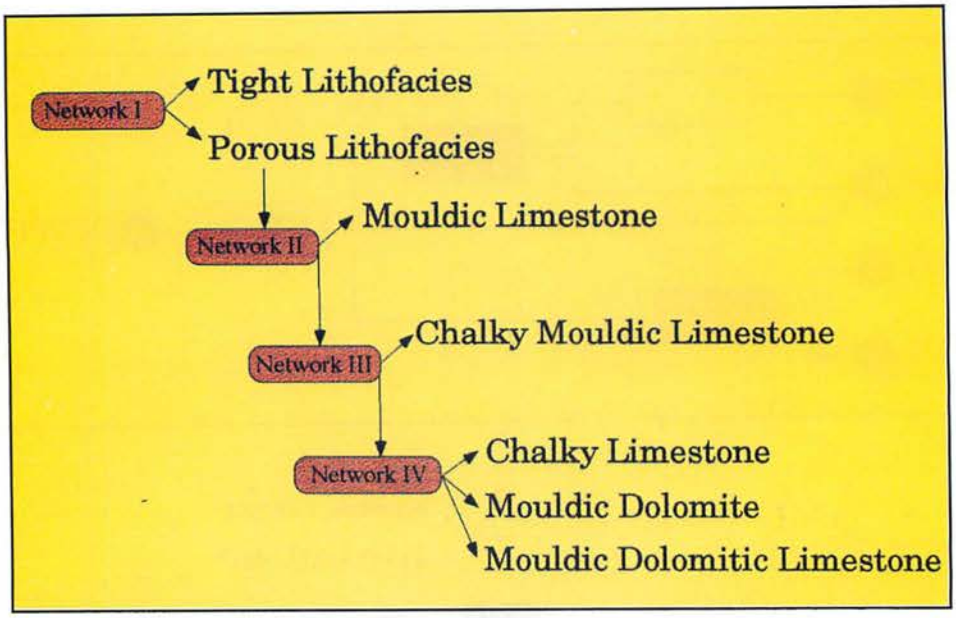

Figure 4. Sequenced network approach for modelling of lithofacies types.

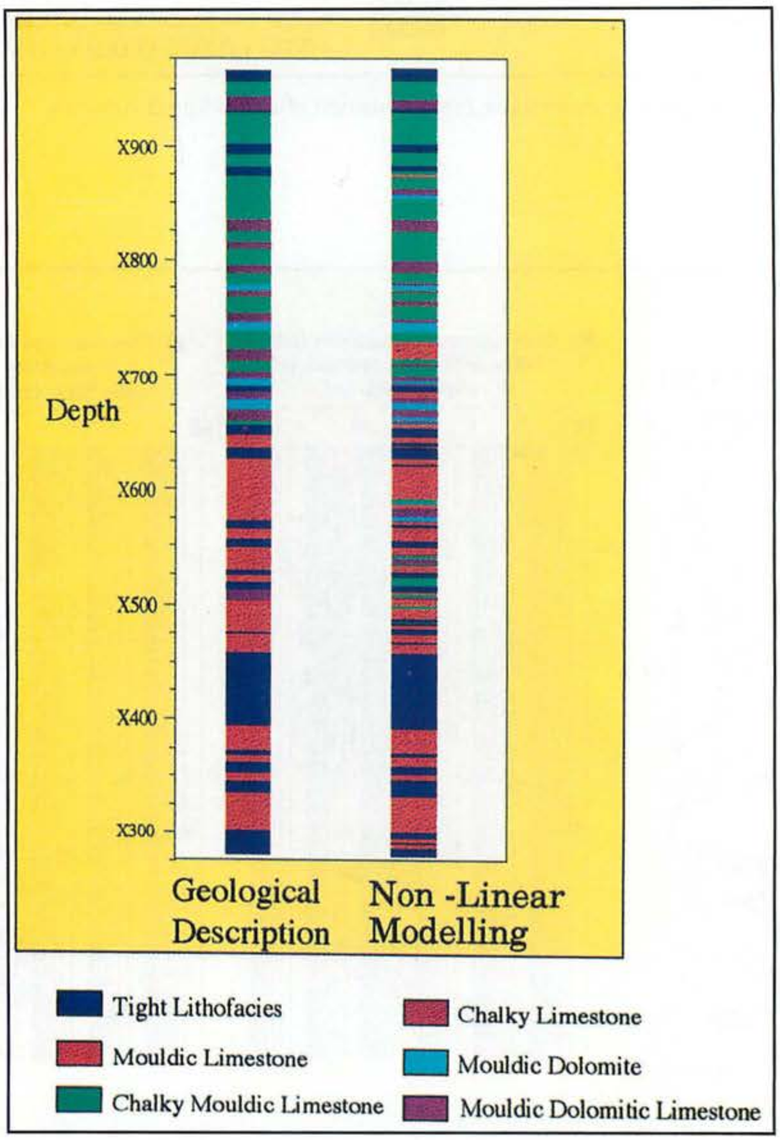

Figure 5. Comparison of modelled lithofacies types with those as described by the geologist.

neutron logs and finally the activity curves for all these logs. The AIM routine randomly samples the training dataset, i.e. depth dependency is not taken into account. In order to include the depth dependency (log character), activity curves were created for each of the open hole logs that are defined as follows:

$$\text{Activity} = 1/L \int_{z=-1/2L}^{z=1/2L} dz(\log \mathit{value}(z) - \mathit{average}\ \log(z))^2$$

Where: L = window length

$$\text{Average } \log(z) = 1/L \int_{z=-1/2L}^{z=1/2L} dz \log \mathit{value}(z)$$

The most effective way of modelling the lithofacies types was by following a sequenced network approach as shown in Figure 4. The first network distinguishes between porous and tight lithofacies. The subsequent network subdivide the porous lithofacies in the lithofacies classes as described by the geologist.

In Figure 5, the geological core description is compared to the network modelled lithofacies types. Although the modelled subdivision is not perfect (mouldic limestone and chalky limestone are difficult to distinguish), approximately 75% of the modelled lithofacies types matches the geological core description, this being a major improvement over conventional techniques that could not make a successful distinction!

CONCLUSIONS

The use of non-linear models improves the characterisation of carbonate rocks compared to conventional techniques. The ability to include a multitude of parameters in the modelling process combined with the ability to use non-linear equations allows a more accurate modelling of permeability and type of lithofacies.

The modelling package AIM can provide a good alternative to existing single/multi variate regression techniques because:

- It is capable of handling a wide variety of information.
- Statistically non-significant parameters are automatically discarded.
- The package is userfriendly and fast.

REFERENCE

AIM SOFTWARE. AbTch Corporation, 700 Harris St., Charlottesville, VA 22901, USA.

Manuscript received 8 December 1993